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Dynamic Planning Methods for Omni-Channel Marketing Resources in the Context of Digital Transformation

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Abstract The rational allocation of marketing resources is the focus of enterprises to increase economic returns. In this paper, we use maximum-minimum, zero-mean and fractional calibration normalization to normalize the enterprise customer data preprocessing and improve the clustering generalization performance. Customers with different characteristics are clustered by K-means algorithm to mine the marketing concerns of similar customers. Combine with the multi-item benefit evaluation formula to calculate the user fitness score and obtain the maximized marketing benefit. Construct the marketing resource model based on information entropy to quantify the marketing resource allocation system loss in order to select the optimal decision variables. The omni-channel marketing resource allocation optimization process of cultural and creative e-commerce stores is exemplified to analyze the effect of this paper's method. The results show that the best classification effect is obtained by clustering customers into six classes and analyzing their corresponding characteristics. After performing the marketing resource optimization, the final product price decreases to RMB 36 per piece, the total sales volume increases to 150*10^4 pieces, the market share increases to 40%, and the profit improves to 16.1%.

Index Terms k-means algorithm, multi-project benefit assessment, user fitness, information entropy, marketing resource allocation

I. Introduction

With the rapid development of the economy and the upgrading of residents' consumption, China's consumer market has undergone radical changes, with both new development opportunities and great competitive pressure [1]. Under the influence of the rapid development of the e-commerce economy, the product operation of some brick-and-mortar stores, due to the existence of higher costs, channel decentralization, and the inability to accurately obtain data and other aspects of the disadvantages, resulting in a more outdated marketing model, but also increase the amount of customer turnover, while making the scale of sales is also shrinking, so that the traditional retail enterprises are facing a great challenge [2]-[5]. In addition, with the development of mobile Internet, the way of consumer shopping is changing, and omni-channel shopping has become a big trend [6], [7]. As a result, retail companies are also combining the Internet and starting the transition from traditional single-channel sales to omni-channel marketing.

Omni-channel marketing, refers to the decision of organizations or individuals to implement channel selection in order to achieve a certain benefit, within the scope of all channels [8]. Its purpose is to make consumers enjoy an undifferentiated shopping experience regardless of the way they purchase goods or services through integration and synergy among channels [9], [10]. Since omni-channel marketing determines both the effect of omni-channel retailing and the specific way of omni-channel retailing, the implementation of omni-channel marketing strategy requires the mutual and effective matching and adjustment between each organization and workflow [11]-[14]. How to fully optimize the allocation of marketing resources between the various organizational structures, give full play to the advantages of online and offline channels, optimize the consumer shopping process, so as to enhance the consumer shopping experience, is particularly important [15]-[17].

Aiming at the problem of mismatch in the unit scale of marketing resources, this paper chooses the maximum-minimum, zero-mean, and fractional calibration normalization methods to preprocess the customer data and improve the data uniformity. K-means clustering analysis is performed on the multi-client data samples to mine various client attributes and enhance the targeting of resource allocation. Establish the data model of marketing projects, use the multi-project benefit assessment formula to score the project-user fitness, and find the benefit maximization path. Based on the information entropy increase amount situation, the marketing resource demand and allocation amount are reasonably optimized, so that the marketing resource allocation system loss is minimized and the economic gain is increased.

II. Analysis of methods related to the optimization of omni-channel marketing resource allocation

This chapter analyzes the clustering algorithm, the multi-project benefit assessment formula, and the marketing resource model based on information entropy, and systematically researches the optimization method of omni-channel marketing resource allocation.

II. A. Market segmentation based on clustering algorithms

II. A. 1) Data normalization

In the process of marketing resource allocation, the unit of each influencing factor is different, for example, the unit of sales volume is 10,000 cases, while the unit of price is yuan, the mismatch in the quantitative outline may cause the unsatisfactory clustering results, so before the clustering results, the data need to be normalized. In this paper, three ways are used to perform data normalization operations, which are: maximum-minimum, zero-mean and fractional calibration normalization.

1) The use of the maximum-minimum normalization operation enables a linear transformation of the original data. Assuming that x_i is the original value of the data, $x_{\max}$ and $x_{\min}$ represent the highest and lowest values of the data on the decision variable R, and letting the standardized value of the normalized data be x_i', x_i' can be expressed as:

$$x_i' = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}; x_{\min} \le x_i \le x_{\max} \tag{1}$$

This normalization maintains the relationship between the raw data as much as possible. If the value of the raw data is not within the range of the maximum-minimum values of the decision variable R, it can be determined that there is a data “out of bounds”.

(2) The zero-mean method is to transform the original data by the mean and standard deviation of the decision variable R. Let the value u of decision variable R be normalized to the standard value u', u' is calculated as follows:

$$u' = \frac{u - \bar{R}}{\sigma_R} \tag{2}$$

In the above equation, $\bar{R}$ is the mean of attribute R and σ_R is the standard deviation of attribute R. The zero-mean normalization method is more effective when there is uncertainty about the maximum and minimum values of the attribute R, or when the data from outlying dissimilarity points happen to be the maximum and minimum values.

3) The decimal normalization method is a data transformation operation on the raw data using the position of the decimal point that moves the data value of the decision variable R. The specific number of decimal places to be moved is determined by the absolute maximum value of the decision variable R. Let the original value u of the decision variable R be u' after transforming by decimal scaling, and u' can be expressed as:

$$u' = \frac{u}{10^k} \tag{3}$$

In the above formula, k is taken to be the smallest integer such that $Max\left(\left|u'\right|\right) < 1$.

II. A. 2) Construct customer clustering based on hierarchical clustering and K-means algorithm

Cluster analysis is the process of dividing a given set of objects into data classes with high data similarity. Among the clustering algorithms based on division, the most widely used is the K-means algorithm.

K-means is the fastest and simplest clustering algorithm. Its basic idea is to set the final data is divided into K clusters, for each data in the dataset, in turn, calculate the Euclidean distance from the data object to the center of the cluster, and categorize it into the cluster with the smallest distance. Generally, data located in the same cluster possess a high degree of similarity between them, and data located in different clusters are more different from each other.

The specific steps of K-means algorithm are as follows:

1) Set the input parameter K as the number of clusters, followed by randomly selecting K data in the given dataset and setting them as the clustering centers of K clusters respectively.

2) Calculate the Euclidean distance di from other data objects in the dataset to the clustering centers of the K clusters in turn, compare them, and categorize this data into the cluster corresponding to the smallest dmin.

3) Once the categorization of the data is complete, the location of the centroid of the cluster needs to be recalculated. Next, the Euclidean distances of the data objects in the data set other than the centroid to the clustering centers of the K clusters are computed sequentially, and the data are re-categorized. This process is repeated until the position of the centroids of the K clusters are no longer changed.

4) Output the final result of clustering.

From the above clustering process of the K-means algorithm, it can be seen that the number of clusters K is an external input, so it is necessary to determine a reasonable parameter value before the clustering algorithm; to determine the initial clustering center of the random sampling method, which leads to the initial clustering center of K-means is very sensitive. Based on these two aspects of the problem, in this paper, the data size is large and the data is time-sensitive, so it is necessary to use the hierarchical clustering method first to get the relevant initialization information of the clustering, such as how many clusters it can be divided into, the location information of the center, etc., and then use the K-means clustering algorithm, in order to improve the efficiency of the clustering algorithm.

The specific clustering steps are as follows:

1) Random sampling of the full set of data for T times. In the process of random sampling of data to try to make the distribution of the sample and the distribution pattern of the whole data consistent.

2) For the sample data set S obtained from random sampling, cohesive hierarchical clustering is performed to determine the number of clusters R and the location of the center point.

3) The centroid determined in the previous step of hierarchical clustering is used as the centroid of the K-means algorithm, and K is used as an input parameter to apply K-means clustering to the whole data.

4) Among the clusters clustered in K groups, the clusters that are close to each other are merged and the center of the clusters is calculated again until the clustering process ends when the number of clusters is reduced to R.

II. B.Multi-Project Benefit Assessment Formula Based on Big Data Modeling

When carrying out accurate marketing for stock operation, it usually establishes a big data model for each project and outputs user suitability scores.

In order to simplify the formula, the formula is deduced by taking the benefit assessment of the 2 project scenarios A and B as an example, and the same for the multi-project scenarios.

The benefit assessment formula for the 2 project scenarios is:

$$\begin{aligned} W &= W_a + W_b = \left(\sum_{i\in A} P_{ai}\times R_{ai} - \tilde{C}_a\right) + \left(\sum_{i\in B} P_{bi}\times R_{bi} - \tilde{C}_b\right) \\ &= \left(\sum_{i\in\{P_{bi}<f(P_{ai})\}} P_{ai}\times R_{ai} - \tilde{C}_a\right) + \left(\sum_{i\in\{P_{bi}\geq f(P_{ai})\}} P_{bi}\times R_{bi} - \tilde{C}_b\right) \\ &= \sum_{i\in\{P_{bi}<f(P_{ai})\}} P_{ai}R_{ai} + \sum_{i\in\{P_{bi}\geq f(P_{ai})\}} P_{bi}R_{bi} - \tilde{C}_a - \tilde{C}_b \end{aligned} \tag{4}$$

where P_{ai} is the fitness score of user i based on the potential user model of item A, reflecting the probability of the user ordering item A; P_{bi} is the fitness score of user i based on the potential user model of item B, reflecting the probability of the user ordering item B; and $f(P_{ai})$ denotes a function with P_{ai} as a function of variables, marketing item B to user i when the condition $P_{bi}\geq f(P_{ai})$ is satisfied, and marketing item A to user i when the condition $P_{bi}<f(P_{ai})$ is satisfied; N_a is the size of the clientele A, i.e., the size of the customer base A that satisfies the condition $P_{bi}<f(P_{ai})$; N_b is the size of the clientele B, i.e., the size of the users that satisfy the condition $P_{bi}\geq f(P_{ai})$; and N is the size of the total users of marketing, $N=N_a+N_b$.

To be meaningful, the benefits must be greater with the introduction of Item B than without the introduction of Item B, and without the introduction of Item B, i.e., all of Marketing A, at which point the benefits are:

$$\begin{aligned} W_0 &= \sum_{i\in N} P_{ai}\times R_{ai} - \tilde{C}_a = \sum_{i\in\{N_a+N_b\}} P_{ai}R_{ai} - \tilde{C}_a \\ &= \sum_{i\in\{P_{bi}<f(P_{ai})\}} P_{ai}R_{ai} + \sum_{i\in\{P_{bi}\geq f(P_{ai})\}} P_{ai}R_{ai} - \tilde{C}_a \end{aligned} \tag{5}$$

The benefit gain of introducing Project B is Eq. (4) - Eq. (5), i.e:

$$S = W - W_0 = \sum_{i \in \{P_a \geq f(P_a)\}} \left(P_{bi}R_{bi} - P_{ai}R_{ai}\right) - \tilde{C}_b$$
$$\cdots \sum_{i \in \{P_a \geq \neq \{P_a)\}} \left[f\left(P_{ai}\right)R_{bi} - P_{ai}R_{ai}\right] - \tilde{C}_b \tag{6}$$

There are 2 marketing objectives introduced into the project B.

a) Eq. (6) is positive, i.e., $S > 0$, then:

$$\sum_{i \in \{P_{bi} \geq f(P_{ai})\}} \left(P_{bi}R_{bi} - P_{ai}R_{ai}\right) \geq \tilde{C}_b \tag{7}$$

b) Eq. (6) takes the maximum value. Since $\tilde{C}_b$ is a fixed value, it is sufficient to demand ≥ 0 for each subterm in the summation term, i.e:

$$P_{bi}R_{bi} - P_{ai}R_{ai} \geq 0 \tag{8}$$

Also due to $P_{bi} \geq f(P_{ai})$, then:

$$f(P_{ai})R_{bi} - P_{ai}R_{ai} \geq 0 \tag{9}$$

Suppose f is a proportional function with:

$$f(P_{ai}) = kP_{ai}, k \neq 0 \tag{10}$$

This can be obtained by substituting Eq. (10) into Eq. (11):

$$(kR_{bi} - R_{ai})P_{ai} \geq 0 \tag{11}$$

Since $P_{ai} \geq 0$, then:

$$k \geq R_{ai} / R_{bi} \tag{12}$$

From Eq. (8), Eq. (10) and Eq. (11), the resource allocation constraints introduced for project B are:

$$P_{bi} \geq R_{\mathrm{ai}}P_{\mathrm{ai}} / R_{\mathrm{bi}} \tag{13}$$

The practical significance of equation (13) is explained below.

a) Principle of marketing resource allocation for 2 projects. After scoring the user fitness of the 2 projects, users whose project scores satisfy Pbi≧RaiPai/Rbi market the new project B, and other users market project A, which can maximize the total project benefits.

b) Project cost assessment and target setting principles. If Project B occupies the marketing resources of Project A, it is necessary to satisfy that the benefit enhancement brought by the resources occupied by Project B is higher than the fixed cost of Project B before Project B has the value of going online. If too few users satisfy the principle of marketing resource allocation, or the value enhancement of B is not enough, the cost cannot be covered and it is recommended to go offline.

c) Key aspect of maximizing benefits. Find a portion of users who have low conversion rate in Project A but high conversion rate in Project B to realize marketing effectiveness enhancement.

II. C.Information entropy-based marketing resource model construction

The assumed demand and allocation of marketing resources are discrete variables, when $m > x$, the allocation of marketing resources is larger than the demand, the marketing resource loss, resulting in an economic cost of $L_1(m-x)$. When the allocation of marketing resources is too much, the result is a systematic loss of marketing resources with an increase in information entropy of ΔH_{L_1}:

$$\Delta H_{L_1} = -L_1(m-x)\sum_{x=0}^{m} p(x)\log_2 p(x) \tag{14}$$

When $m < x$, the amount of marketing resources allocated is smaller than the amount of demand, and it is impossible to satisfy the amount of marketing resources demanded, incurring an economic cost of $L_2(m-x)$, and the increase in information entropy of the marketing resource allocation system due to the shortage of marketing resources is ΔH_{L_2}:

$$\Delta H_{L_2} = -L_2(m-x)\sum_{x=0}^{m} p(x)\log_2 p(x) \tag{15}$$

Based on the above two equations, we can derive the increase in the total information entropy of the marketing resource allocation system loss ΔH:

$$\Delta H = \left[-L_1(m-x)\sum_{x=0}^{m} p(x)\log_2 p(x)\right] + \left[-L_2(x-m)\sum_{x=m}^{\infty} p(x)\log_2 p(x)\right] \tag{16}$$

When the decision variables are chosen optimally, the increase in the information entropy of the loss of the marketing resource allocation system will be minimized. In this case, the following condition should be satisfied $m = m^*$:

$$\left.\frac{d\Delta H}{dm}\right|_{m=m^*} = 0 \tag{17}$$

Substituting Eq. (16) into Eq. (17) while letting $H_0 = -\sum_{x} p(x)\log_2 p(x)$ be the information entropy of the demand for discrete marketing resources x, then:

$$\begin{aligned}
&\left[-L_1(m-x)\sum_{x=0}^{m} p(x)\log_2 p(x)\right] + \left[-L_2(x-m)\sum_{x=m}^{\infty} p(x)\log_2 p(x)\right] = 0 \\
&-L_1 m\sum_{x=0}^{m} p(x)\log_2 p(x) + L_1 x\sum_{x=0}^{m} p(x)\log_2 p(x) \\
&-L_2 x\sum_{x=\infty}^{\infty} p(x)\log_2 p(x)dx + L_2 m\sum_{x=m}^{\infty} p(x)\log_2 p(x) = 0 \\
&\sum_{x=0}^{m} p(x)\log_2 p(x)(L_1+L_2) = L_2 H_0
\end{aligned} \tag{18}$$

Let $m = m^*$ at this point be derived:

$$H(m^*) = \sum_{x=0}^{m^*} p(x)\log_2 p(x) = \frac{L_2 H_0}{L_1 + L_2} \tag{19}$$

Replace L_1 and L_2 with L_{11}, L_{12}, L_{21}, and L_{22}. It can be obtained:

$$H(m^*) = \sum_{x=0}^{m^*} p(x)\log_2 p(x) = \frac{(L_{21}+L_{22})H_0}{L_{11}+L_{12}+L_{21}+L_{22}} \tag{20}$$

III. Omni-channel marketing resource allocation optimization practice

This chapter takes the data of the cultural and creative e-commerce store A as the research object, preprocesses and clusters its customer data, and carries out marketing resource allocation practice according to the analysis results, comparing the effect of resource allocation optimization method in this paper.

III. A. Data pre-processing

Taking the omni-channel marketing of cultural and creative e-commerce store A as an example, the customer data of the last 3 years are preprocessed. A total of eight feature variables, including age, monthly income, geographic region, number of products purchased, gender, historical consumption amount, positive feedback rate, and historical consumption times, are extracted. In order to improve the model performance and generalization ability, identify redundant features, avoid model overfitting, and optimize feature selection. In this section, Pearson correlation analysis is applied to analyze the correlation of feature variables in the data sample. The feature quantities with correlation greater than 0.5 are defined as strong correlation indicators, and then the features are filtered by feature importance indicators.

Figure 1 shows the obtained correlation coefficients of feature variables. Figure 2 is the result of ranking the importance of data feature variables. From the feature correlation graph, we can see that the feature amount of historical consumption amount and historical consumption number reaches 0.5, which is defined as a strong correlation indicator. Through the feature importance scores, we can see that in the process of predicting whether a customer will make an order or not, the number of products purchased has the highest importance (0.29), the amount of historical consumption (0.20) is the second most important, the monthly income (0.13), age (0.11), geographic area (0.11), positive feedback (0.11), and the number of historical consumption (0.05) are again the second most important, and the gender basically shows no Related. Among the customers of cultural and creative goods, according to the development research report of China's cultural and creative and gift economy industry, female customers account for more than 50%, but on Taobao platform, in order to protect the privacy of users, merchants are unable to see the real gender of the customers, and the gender shown is the virtual gender of Taobao platform, and the male-to-female ratio is almost 1:1, so it is shown to be almost irrelevant in the process of analyzing the importance of the characteristic variables. In order to exclude the interference caused by irrelevant variables, we remove the feature variable of gender from the data table. At the same time, combined with the feature correlation analysis, we see that in the feature importance, the historical consumption amount is much larger than the historical consumption number. Therefore, we remove the feature quantity of historical consumption times.

Combined with the data feature importance and feature correlation analysis results for feature screening, we initially selected 6 features as the basis for customer classification, including the number of products purchased, historical consumption amount, monthly income, age, geographic region, and positive feedback rate. And according to these 6 features, the sample data are normalized and preprocessed to get the sample data that can be used for cluster analysis.

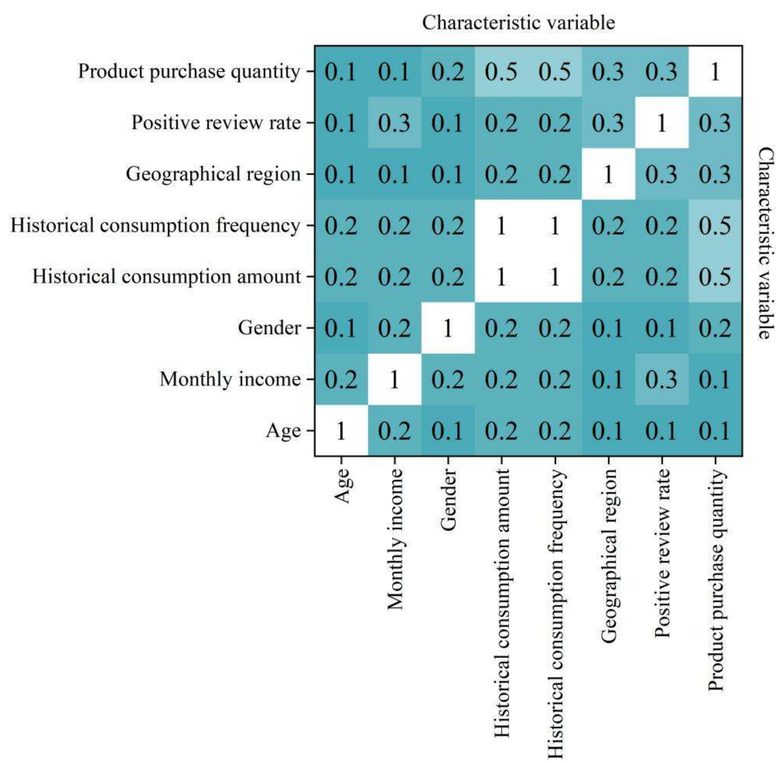

Figure 1: Feature Correlation Plot

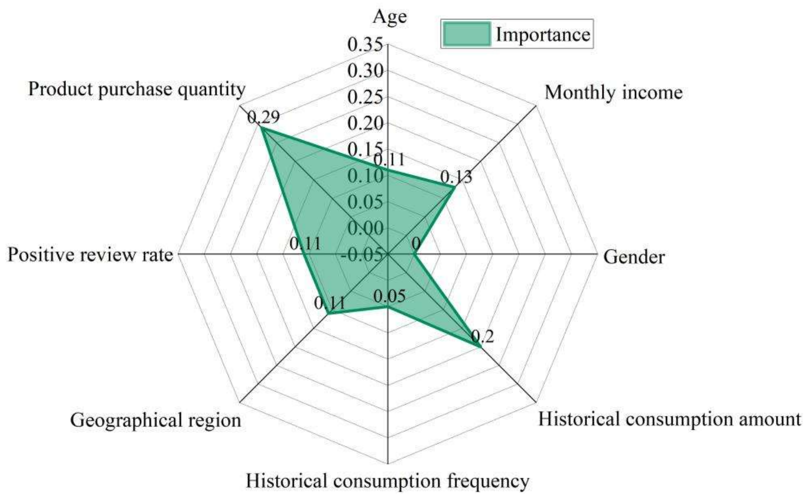

Figure 2: Sorting result

III. B. Cluster analysis

III. B. 1) Initial clustering results

After extracting the data with six features and normalizing them, K-means clustering analysis can be performed. The data of the six features after normalization is used as the customer segmentation variable, because the size of the k-value will have a large impact on the results of the cluster analysis, considering that the number of customer segments of the cultural and creative e-commerce store A should be between two and eight, for the determination of the k-value, the calculation results of multiple attempts at different values can be compared to find out the optimal value. This paper also adopts the method of minimizing the distance within categories and maximizing the distance between categories, and after many attempts, when the k value is 6, it is consistent with the minimization of the distance within categories and the maximization of the distance between categories, so the k value of 6 is the best choice of the number of customer data clusters.

For the clustering analysis of the normalized data of the customers of the cultural and creative e-commerce store A, the maximum number of iterations is set to 100, and the convergence is set to 0 under the condition of the clustering number of 6. Table 1 shows the initial clustering center of the K-means clustering algorithm. Considering that the K-means clustering analysis method does not supervise and control the clustering process, and there is no way to predict the result of the final classification of the sample data, this kind of randomly selected clustering centers is generally applicable to the segmentation of the customers of e-commerce store A in the cultural and creative category. From the initial clustering center, it can be seen that there is a big difference in the influence size of the 6 customer features on the clustering effect, and the center of mass position of the clustering center for each 1 customer feature is different. For example, the location of the center of mass in cluster categories 1 and 2 is on the quantity of products purchased feature, while the location of the center of mass in cluster categories 5 and 6 is on the historical consumption amount feature. Since these are initial clustering centers, continuous iteration is required to obtain the final clustering centers.

Table 1: Initial clustering center

K	Cluster					
	1	2	3	4	5	6
Age	2.15348	0.53215	-0.60113	3.21525	0.52173	0.42126
Monthly income	3.15285	-0.0892	-1.80115	2.32851	0.62995	0.52692
Geographical region	4.69861	0.63015	-1.85982	4.14012	1.08192	0.88094
Positive review rate	-1.39896	0.69981	-0.69895	0.69985	-1.39885	0.99347
Historical consumption amount	-0.72983	-1.19930	-2.14981	-0.73303	4.46581	2.46682
Product purchase quantity	11.5703	10.78013	-0.35014	0.04610	0.59883	0.79837

III. B. 2) Final clustering results

Table 2 shows the final clustering center results. Comparison of Tables 1 and 2 reveals that the location of the center of mass of the initial and final clustering centers has changed significantly. Cluster 1's center of mass location is in the number of products purchased feature (7.38258), Cluster 2's center of mass location is in the geographic region feature (2.75151), Cluster 3's center of mass location is in the positive feedback rate feature (-0.00596), Cluster 4's center of mass location is in the age feature (1.41233), Cluster 5's center of mass location is in the historical consumption amount feature (1.05403), Cluster 6 's center of mass location in monthly income feature (3.53721). It shows that the effect of cluster analysis is significant and can effectively differentiate the customers of e-commerce store A of cultural and creative industries according to different features.

Table 2: Final clustering center

K	Cluster					
	1	2	3	4	5	6
Age	1.15348	0.73212	-0.70111	1.41233	0.72314	0.52115
Monthly income	1.92933	1.51823	-1.08364	0.51526	0.11772	3.53721
Geographical region	3.02280	2.75151	-0.98172	0.27921	0.16235	0.63092
Positive review rate	0.12792	0.12956	-0.00596	-0.04064	0.04532	0.86346
Historical consumption amount	0.75635	0.86502	-0.22077	-0.64505	1.05403	1.26180
Product purchase quantity	7.38258	1.48985	-0.24822	-0.23310	0.88471	0.67361

III. B. 3) Customer profiling based on clustering results

Take the number of products purchased as an example to analyze the customer characteristics under the clustering results. The results of the clustering analysis of the customers of the e-commerce store A in the cultural and creative category show that, with regard to the characteristic of the number of products purchased by the customers in store A, the coverage of the distribution of the number of products purchased ranges from 10 to more than 1,000 pieces in 30,000 pieces of customer data, with an average number of products purchased of about 400 pieces. Figure 3 shows the combination of the average number of products purchased and the cumulative weight of the number of products purchased. The number of customers whose product purchase quantity is more than 400 pieces is about 500, which only accounts for 16.7% of the total number of customers, but the product purchase quantity of this group of customers accounts for more than 40% of the total number of products sold in the store. It can be seen that the main sales target of the cultural and creative e-commerce store A is this type of customers with large purchases, and when allocating marketing resources, it should focus on the needs of this part of the customers.

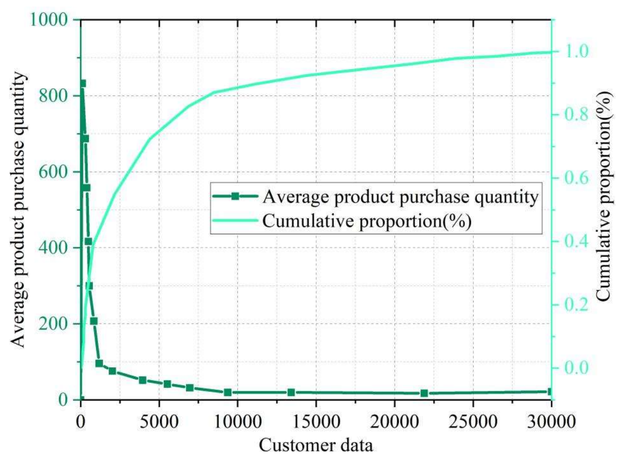

Figure 3: Average purchase quantity and cumulative proportion

III. C. Marketing resource allocation optimization and result analysis

Based on the results of customer clustering and feature analysis, the marketing resource model constructed is combined to optimize the marketing resource allocation of cultural and creative e-commerce store A during omni-channel marketing. In order to judge the optimization effect of the marketing resource model, the same type of alternatives A1 and A2 in store A are selected for marketing resource allocation experiments. Commodity A1 still continues the original marketing means, and commodity A2 uses the method of this paper to optimize the allocation of marketing resources.

Table 3 shows the marketing resource allocation as well as the change in sales volume of the two types of commodities after the experiment. Table 4 shows the marketing results of the 2 types of commodities for 4 consecutive quarters. From the final marketing results in Table 3 and Table 4, Commodity A1, as the control commodity, follows the traditional marketing resource allocation scheme, with a final product price of 40 yuan per piece, a total sales volume of $80*10^4$ pieces, and no change in market share and profit growth. While A2 goods using the method of this paper to make a reasonable allocation of marketing resources, the final product price of 36 yuan / piece, the total sales volume of $150 * 10^4$ pieces, the market share in four quarters of growth, from the original 35% to 40%, profit from the original 12% to 16.1%. Through the effective allocation of marketing resources, A2 commodities gained higher economic returns while marketing costs were reduced. This also verifies the optimization effect of the method in this paper.

Table 3: The change in sales volume before and after optimization

Marketing resources	A1	A2
Advertising expense A (10^4 yuan)	1800	750
Promotion expense S (10^4 yuan)	600	1350
Product price P (yuan)	40	36
Total sales volume Q (10^4 pieces)	80	150

Table 4: The marketing and sales results of the fourth quarter

	A1	A2	A2 Market share (%)	A2 Profit growth (%)
Quarter 1	Original	Original	35	12.0
Quarter 2	Unchanged	Growth	37	15.3
Quarter 3	Unchanged	Growth	38	15.9
Quarter 4	Unchanged	Growth	40	16.1

IV. Conclusion

This paper integrates K-means clustering algorithm and information entropy method to characterize the marketing target users and targeted resource allocation to improve the digital development of enterprises. Through clustering analysis, the customer data is categorized into 6 categories, in which the number of customers who purchase products in large quantities only accounts for 16.7% of the total number of customers, but the purchase volume accounts for more than 40% of the total number of products sold in the store, which needs to be focused on during marketing resource allocation. The optimized allocation of marketing resources reduces the price of goods, but the total sales volume increases to $150*10^4$ pieces. And the market share of this category of goods has been increasing to 40% in 4 quarters, which is 5% more than the original 35%. Profit increased to 16.1%, an increase of 4.1% from the original 12%. The optimal allocation of omni-channel marketing resources to the enterprise's goods can achieve the goal of reducing marketing costs and improving marketing efficiency. In the future, a deep learning mechanism can be introduced into the model to dig deeper into the pain points of different types of customer needs and improve the effect of marketing resource allocation.

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